

UNCLASSIFIED

Defense Technical Information Center
Compilation Part Notice

ADP023094

TITLE: Tracker Performance Metric

DISTRIBUTION: Approved for public release, distribution unlimited

This paper is part of the following report:

TITLE: Proceedings of the Ground Target Modeling and Validation
Conference [13th] Held in Houghton, MI on 5-8 August 2002

To order the complete compilation report, use: ADA459530

The component part is provided here to allow users access to individually authored sections of proceedings, annals, symposia, etc. However, the component should be considered within the context of the overall compilation report and not as a stand-alone technical report.

The following component part numbers comprise the compilation report:

ADP023075 thru ADP023108

UNCLASSIFIED

Tracker Performance Metric

Teresa Olson, Harry Lee and Johnnie Sanders
Lockheed Martin Missile and Fire Controls

ABSTRACT

Currently, there is no standard quantitative measure of the performance of an image-based tracker algorithm. It is usually described as remaining in track for the entire run or losing track at some point during a run. This is purely a qualitative evaluation. Without a quantitative measure it becomes difficult to accurately evaluate the performance of a tracker algorithm. We have developed the Tracker Performance Metric (TPM) specifically for this purpose. It was designed to measure the output performance, on a frame-by-frame basis, using its output position and quality (sometimes referred to as confidence) state. The TPM can also be used as a measure of algorithm performance to compare against the Trackability Metric. The Trackability Metric was developed by AMCOM to determine how "trackable" a set of data should be. The TPM will be described and results presented.

Keywords: Tracker Performance Metric, Aimpoint Selection Metric, Quality Measure

INTRODUCTION

The purpose of this paper is to introduce a family of functions designed to yield standard quantitative calculations to rate performance for image-based tracker and aimpoint selection algorithms. These functions are adaptable to the algorithm evaluator's desired output requirements. They also have the ability to exploit composite tracker and aimpoint algorithm technology that may be used to leverage multiple algorithms within a solution suite. This approach requires a component track quality measure that represents the algorithm's inferred performance. We believe that a quality metric is an extremely important output of any tracker algorithm for producing robust solutions for today's military environment. An algorithm's ability to accurately assess its current quality state is a crucial metric for confidence measures that enable internal corrections and aid in external guidance decisions. If an evaluator does not have the ability to measure the quality of his tracker algorithm, the quality factor can be input as the maximum value of one. However, we must stress that this would not be considered an optimal solution. An accurate quality measure provides the most effective representation of tracker performance.

METRIC FORMULATION

At the center of this metric concept is the proposed function $f(x, y; Q, x_o, y_o)$, where (x, y) are image coordinate variables, Q is the algorithm's internally assessed quality metric (constrained by $0 < Q \leq 1$) and (x_o, y_o) is the algorithm's position output. The function is assumed to be integrable over all space, "centered" at the algorithm output position (x_o, y_o) , and normalized to unit area ($\iint_{\text{all space}} f(x, y; Q, x_o, y_o) = 1$). The metric is calculated by integrating this function over

the desired area of interest (A_D), typically centered on the true target location (x_T, y_T) . In mathematical form, the performance metric is represented by $TPM = \iint_{A_D} f(x, y; Q, x_o, y_o)$. Because of the normalization criteria, the TPM is guaranteed to produce a value between zero and one ($0 \leq TPM \leq 1$).

The TPM was developed to be used in conjunction with the Trackability Metric (TM) or Gray Level Co-occurrence Matrix (GLCM). For detailed information on the TM, we refer the reader to [1,2,3]. The Trackability Metric measures how well a tracker should perform based on the tracker's frame-by-frame input imagery. On the other hand, the Tracker Performance Metric measures how well a tracker actually does perform on a frame-by-frame basis. Because both functions are normalized to the same scale (0-1), they are easily comparable. In general, a robust tracker would be expected to perform equal to or better than the GLCM representation.

To illustrate the utility of this proposed metric, it is simpler if we select a typical example of a set of desired output requirements for an algorithm. We will then be able to choose a representative for the function $f(x, y; Q, x_o, y_o)$ and the appropriate area of interest for integration. A typical performance goal for an image-based tracker is to reference all outputs to the centroid of the target under track. Large deviations of the tracker output from this centroid should be penalized as well as incorrect internal assessments of the tracker's quality measure. We have selected the area of interest as the entire target area but internal regions within the target itself are also viable candidates (especially for aimpoint selection evaluations). To review, we want to penalize tracker output deviations from the centroid of the target and also incorrect internal assessments produced from the tracker's quality metric evaluation.

In order to demonstrate this concept, choose the desired area of interest, A_D , to be a rectangular shaped target truth box having dimensions (L_x, L_y) that tightly encompass the target and is centered on the target centroid. Note that this region does not have to be rectangular. It could also be chosen to reflect the true target segment. As we will show later, choosing a rectangular region simplifies the computation. For our function, we choose a 2-dimensional multivariate

Gaussian (normal) distribution, $N(\bar{r}; \bar{\mu}, \Sigma)$, centered at the tracker's output position $\bar{\mu} = \begin{bmatrix} x_o \\ y_o \end{bmatrix}$ with matrix

$$\Sigma = \begin{bmatrix} \left(\frac{L_x}{6Q}\right)^2 & 0 \\ 0 & \left(\frac{L_y}{6Q}\right)^2 \end{bmatrix}, \text{ where } \bar{r} = \begin{bmatrix} x \\ y \end{bmatrix} \text{ and } 0 < Q \leq 1 \text{ is the confidence measure output of the tracker. The choice}$$

of the diagonal elements of Σ comes from our desire to have at least 99% of the area under the Gaussian surface contained within the target truth box when the Q value equals one ($\frac{L_x}{2Q} = 3\sigma; \frac{L_y}{2Q} = 3\sigma$). This gives the following functional form for $N(\bar{r}; \bar{\mu}, \Sigma)$:

$$\begin{aligned} N(\bar{r}; \bar{\mu}, \Sigma) &= \frac{1}{2\pi |\Sigma|^{0.5}} \exp\left(-\frac{1}{2}(\bar{r} - \bar{\mu})^T \Sigma^{-1} (\bar{r} - \bar{\mu})\right) \\ &= \frac{1}{2\pi \left(\frac{L_x L_y}{36Q^2}\right)} \exp\left(-\frac{(x - x_o)^2}{2\left(\frac{L_x}{6Q}\right)^2} - \frac{(y - y_o)^2}{2\left(\frac{L_y}{6Q}\right)^2}\right) \\ &= \frac{1}{\sqrt{2\pi \left(\frac{L_x}{6Q}\right)^2}} \exp\left(-\frac{1}{2} \frac{(x - x_o)^2}{\left(\frac{L_x}{6Q}\right)^2}\right) \cdot \frac{1}{\sqrt{2\pi \left(\frac{L_y}{6Q}\right)^2}} \exp\left(-\frac{1}{2} \frac{(y - y_o)^2}{\left(\frac{L_y}{6Q}\right)^2}\right) \\ &= N\left(x; x_o, \left(\frac{L_x}{6Q}\right)^2\right) \cdot N\left(y; y_o, \left(\frac{L_y}{6Q}\right)^2\right) \end{aligned}$$

The TPM is calculated by integrating this normal distribution only over the portion of the image that the target occupies. For a rectangular truthed region, A_D , this is represented by the following equation:

$$\begin{aligned}
TPM &= \iint_{\text{target}} N(\bar{r}; \bar{\mu}, \Sigma) dA = \iint_{\text{target}} N\left(x; x_o, \left(\frac{L_x}{6Q}\right)^2\right) \cdot N\left(y; y_o, \left(\frac{L_y}{6Q}\right)^2\right) dx dy \\
&= \left(\int_{\text{target}} N\left(x; x_o, \left(\frac{L_x}{6Q}\right)^2\right) dx \right) \cdot \left(\int_{\text{target}} N\left(y; y_o, \left(\frac{L_y}{6Q}\right)^2\right) dy \right) \\
&= \frac{1}{2} \left(\operatorname{erf}\left(\frac{x_2 - x_o}{\sqrt{2\left(\frac{L_x}{6Q}\right)^2}}\right) - \operatorname{erf}\left(\frac{x_1 - x_o}{\sqrt{2\left(\frac{L_x}{6Q}\right)^2}}\right) \right) \cdot \frac{1}{2} \left(\operatorname{erf}\left(\frac{y_2 - y_o}{\sqrt{2\left(\frac{L_y}{6Q}\right)^2}}\right) - \operatorname{erf}\left(\frac{y_1 - y_o}{\sqrt{2\left(\frac{L_y}{6Q}\right)^2}}\right) \right)
\end{aligned}$$

where $L_x = x_2 - x_1 > 0$, $L_y = y_2 - y_1 > 0$ and $\operatorname{erf}(x) = \frac{2}{\sqrt{\pi}} \int_0^x \exp(-t^2) dt$ is the standard error function used by Matlab (erf.m).

The crucial element in this formulation is that the function should be “centered” around the algorithm’s output track point but the integration should only be taken over the desired area of interest. A mixture model of Gaussians matched to predefined lethality maps could be used to effectively quantify tracker performance in a more sophisticated aimpoint selection evaluation mode. As the output drifts away from the desired area or the tracker’s quality metric becomes inaccurate, the area under $f(x, y; Q, x_o, y_o)$ will move away or expand into or out of region A_D .

EXAMPLES

Figure 1 illustrates TPM results for a tracker on US Army Aviation and Missile Command (AMCOM) data. The images show the truth bounding box and the 1-sigma, 2-sigma and 3-sigma ellipses of the normal distribution. In the left image, the TPM = 0.97 because the tracker’s output is located near the center of the target and the tracker has a high confidence value. The right image has a TPM = 0.881, even though the output is located near the center of the target. This is because the tracker’s quality (Q or TQ) is equal to 0.707. This has allowed more of the area to bleed outside of A_D . By design, a tracker producing an output on the target centroid, having a high degree of confidence (TQ = 1) will give a TPM approximately equal to one.

Tracker Performance Metric

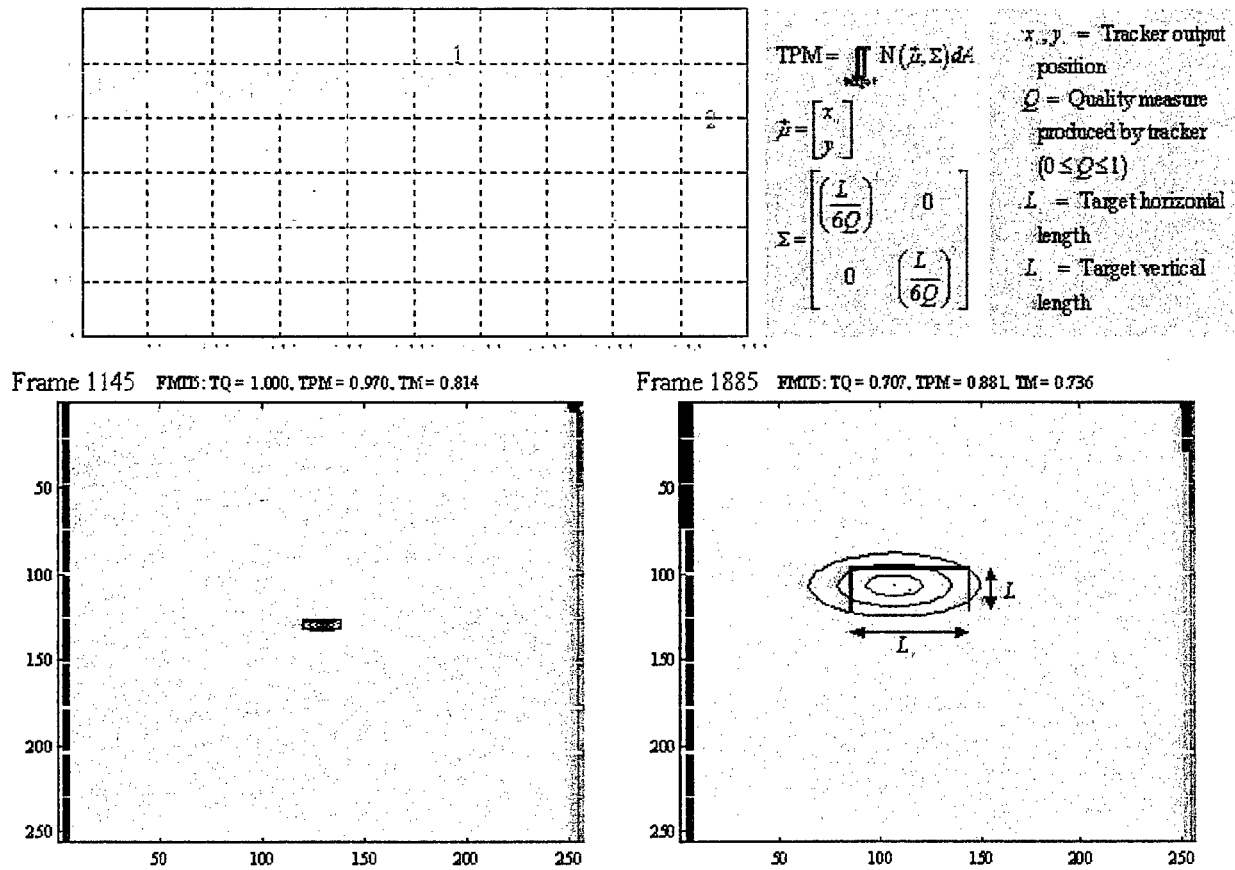


Figure 1: Tracker Performance Metric example 1.

Figure 2 illustrates TPM results for another tracker run on a different data set. Note the right image. The TPM has the very low value of 0.088. Not only has the tracker produced an output on this frame far from the target centroid, but also it is claiming a relatively high confidence of being on track (0.739). This is a problematic result for the tracker. The tracker is claiming good performance but actually producing poor results. Note that had the tracker been reliable enough to claim a poor quality rating, the ellipses would have expanded outward from the tracker output and towards the desired region of interest (the target). This would have yielded more area over the target region, and therefore, a higher TPM value. This result is fundamental to our metric formulation. Because the tracker has a better understanding of its performance limitations, it is more reliable and the algorithm performance metric reflects it. If the tracker can accurately identify when it has a lower confidence or quality, it can potentially indicate when to go into track or when not to update temporal information. A tracker that makes good assessments regarding its internal state, yields more accurate guidance decisions, and therefore, more accurate system results.

Figure 3 shows an example of the Tracker Performance Metric plotted against the Trackability Metric. It can be seen that the TPM corresponds well with the GLCM TM.

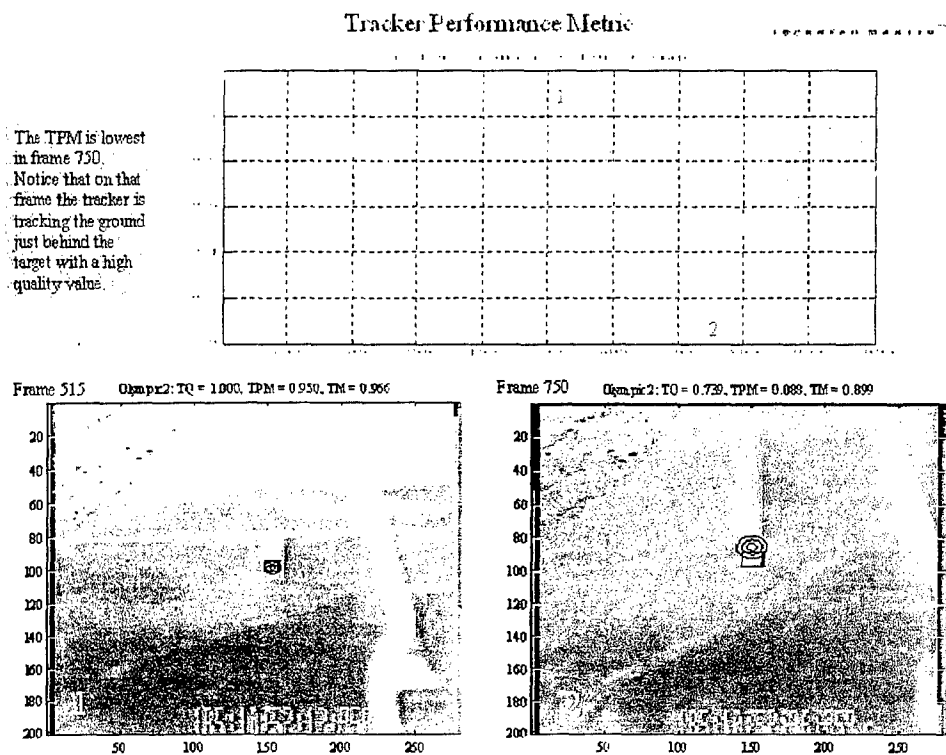


Figure 2: Tracker Performance Metric example 2.

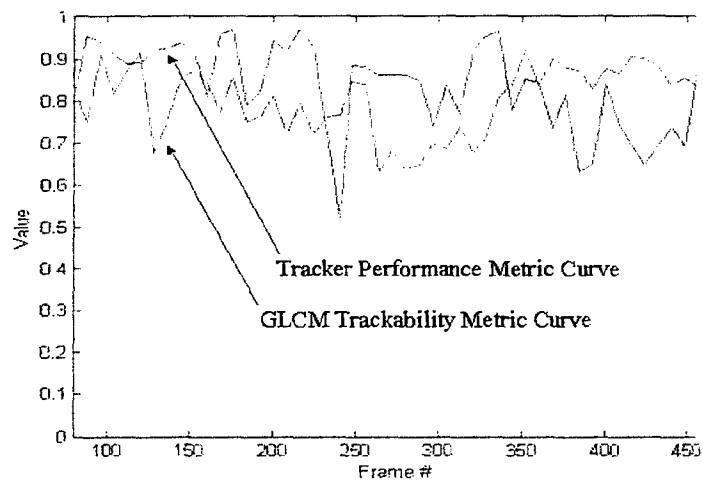


Figure 3: Tracker Performance versus Trackability Metric example.

SUMMARY

This paper has derived a quantitative method for evaluating the performance of any image-based tracker algorithm. This method, known as the Trackability Performance Metric, can be used to compare the performance of two or more independent tracker or aimpoint algorithms. It can also be used in conjunction with the Gray Level Co-occurrence Matrix Trackability Metric to determine how well a given algorithm performs verses how well it should perform on a given set of data.

ACKNOWLEDGEMENTS

The authors would like to thank Jamie Cannon, Kim Pham and Quang Tran for their dedicated work in truthing imagery and implementing the algorithms in Matlab. They would also like to thank Dr. Richard Sims from US Army Aviation and Missile Command (AMCOM), Redstone Arsenal, Alabama for providing the imagery being used in this metric development as well as Dr.'s Monte Helton and Ricky Hammon for providing the Trackability Metric code.

REFERENCES

1. Monte K. Helton, Ricky Hammon and Brian Brackney, "The development of the gray-level co-occurrence matrix target trackability metric for imaging missile systems", Proc. IRIS Passive Sensors, 1998, Vol. 1, pp. 195-207.
2. Brian A. Brackney, Monte K. Helton, and Ricky K. Hammon, "Development of the Gray-Level Co-occurrence Metric Target Trackability Metric for Imaging Infrared Missile Systems", SPIE Proceedings, Image Processing, Vol. 3377, 240-254, Orlando, FL, 1998.
3. Robert L. Hall, Ricky K. Hammon, Brian A. Brackney, and Benjamin J. Schmid, "Design Modifications to the Gray-Level Co-occurrence Matrix (GLCM) Based Trackability metric and the Resulting Performance", SPIE Proceedings, Image Processing, Vol.4365, 34-45, Orlando, FL, 2001.